European Journal of Electrical Engineering and Computer Science
Vol 8 | Issue 3 | May 2024
ISSN 2736-5751

RESEARCH ARTICLE

A Comprehensive Artificial Intelligence-Driven Healthcare System

Frank Edughom Ekpar*

ABSTRACT

The World Health Organization (WHO) states that millions of people worldwide suffer from severe health conditions like diabetes, cardiovascular diseases, stroke, autism, and epilepsy. Some of these conditions, like diabetes, have been on the rise in low-and middle-income countries (LMICs) recently. These conditions have a significant impact on mortality, disability, economic losses, and physical and emotional suffering. However, with more accurate diagnosis, early detection, and prediction of occurrence, these conditions can be treated and managed more effectively, and in some cases, even prevented. This paper presents a comprehensive healthcare system that utilizes artificial intelligence (AI), including large language models (LLMs)–such as Bard and GPT-4 (and their improved future variants), deep learning neural networks, and machine learning platforms such as TensorFlow, electronic health records (EHR), as well as conventional and innovative three-dimensional multilayer EEG systems. The system permits the incorporation of genetic, lifestyle, and environmental information that provides more accurate representations of the participant's environment and leads to improved health outcomes. This will provide actionable insights for clinical decision support in the early detection, diagnosis, treatment, management, prediction, and prevention of various conditions, including diabetes, cardiovascular diseases, stroke, autism, and epilepsy-saving lives and improving living conditions by reducing the economic, social, psychological and physical burden of the conditions so predicted and possibly prevented, detected early, diagnosed, treated and managed more efficiently. Additionally, the system aims to facilitate practical human-machine interfaces (HMIs) such as brain computer interfaces (BCIs) and progress towards computer-mediated brain-to-brain communication. It also seeks to enhance our understanding of the human brain's functioning in both normal and diseased states, which can be used for the rehabilitation of individuals with neurological conditions and to create innovative ways for healthy individuals to interact with their environment and improve their lives.

Keywords: Artificial Intelligence (AI), Disease Diagnosis and Prediction, Healthcare System, TensorFlow.

Submitted: March 20, 2024
Published: May 13, 2024

10.24018/ejece.2024.8.3.617

Scholars University Ltd; Rivers State University; Topfaith University, Nigeria.

****Corresponding Author:***
e-mail: frank@scholarsuniversity.org

1. Introduction

Millions of people around the world suffer from debilitating conditions such as diabetes, cardiovascular diseases, stroke, autism, and epilepsy [1]–[4]. The prevalence of some of these conditions (diabetes for example) has been on the increase in low-and middle-income countries (LMICs) in recent times. These conditions exert an incalculable burden in terms of mortality, disability, economic losses, and physical and psychological suffering. However, with more accurate diagnosis, early detection, and the prediction of the likelihood of occurrence, these conditions can be treated and managed much more efficiently and even prevented altogether–saving countless lives and significantly improving the human condition.

Researchers have applied AI to the diagnosis and prediction of diseases such as diabetes and other conditions [5]–[23] mainly in developed countries, making the results susceptible to bias while limiting their global relevance.

The application of large language models (LLMs) [24], [25] with the ability to draw inferences using AI models trained on input data and to learn structured representations of the underlying data to the prediction and diagnosis of health conditions and the construction of BCIs is not yet widespread.

Furthermore, brain-computer interfaces (BCIs) based on a variety of paradigms including the motor imagery paradigm have been developed using a wide range of AI platforms and architectures including convolutional neural networks (CNNs) as well as traditional techniques such as principal component analysis [26]–[44]. For BCIs based on electroencephalography (EEG) data, the use of novel three-dimensional multilayer EEG systems [45], [46] can provide improved performance.

The comprehensive AI-driven healthcare system presented here is characterized by a modular architecture with dedicated modules for specific conditions. New modules can be added to the system while existing modules can be enhanced with fresh data and improved algorithms.

Highlighted in this paper is the implementation of the Heart Disease Diagnosis Module of the comprehensive AI-driven healthcare system.

2. Materials and Methods

2.1. *Participant Recruitment*

Participants volunteered to take part in the studies leading to the development of the comprehensive AI-driven healthcare system and each participant gave informed consent for participation in the studies.

2.2. *Ethical Approval*

The Health Research Ethics Committee of the Institute of Biomedical Research at the University of Uyo provided ethical clearance/approval for the studies. The studies complied with all relevant ethical and regulatory requirements. Publicly available data were utilized in accordance with the licensing provisions stipulated by their creators.

2.3. *Methodology*

Publicly accessible healthcare datasets could be enhanced by incorporating datasets gathered through local experiments and data collection efforts and used to train AI models to make actionable predictions from new data. Public sources of healthcare datasets include the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society and Kaggle.

The incorporation of local data ensures robustness, reduces bias and promotes inclusivity and global relevance.

Combining diagnostic measurements (which may include electrocardiographic results) from local experiments with EEG data (both from conventional and novel three-dimensional multilayer EEG systems) is one of the unique approaches adopted in this project.

For local data acquisition drives, the research has obtained ethical approval/clearance from research ethics committees overseeing the geographic region where the experiments are conducted. Additionally, access to decision-makers' time has been secured through licensed medical doctors with experience in the relevant areas. These doctors have direct access to patients and other clinicians in the community and are partnering with the project to provide anonymized clinical measurements for the validation of the AI models.

The trained AI models are then integrated into a comprehensive healthcare system designed to offer clinical decision support to medical practitioners and for the generation of BCIs. This support will be based on actionable predictions and insights generated from new clinical data provided by the medical practitioners. This will aid in the early detection, diagnosis, treatment, prediction, and prevention of a wide range of conditions, including diabetes, cardiovascular diseases, stroke, autism, and epilepsy.

This project is committed to the furtherance of open science, reproducibility, and collaboration. Consequently, the data generated will be uploaded to public repositories such as GitHub.

2.4. *System Design and Implementation*

The comprehensive healthcare system presented in this paper features a modular architecture with each condition (diabetes, cardiovascular diseases, stroke, epilepsy, autism, and so on) assigned to a separate module, making the system applicable to the diagnosis and prediction of additional conditions in the future and facilitating efficient modifications to existing modules using fresh data. Modules for BCIs such as those based on the motor imagery paradigm could accept EEG data and generate actionable commands and other suitable responses.

The system incorporates a set of instructions detailing the adaptation of conventional EEG systems to novel three-dimensional multilayer EEG systems. Novel three-dimensional multilayer EEG systems created by Ekpar [31], [32] are based on a conceptual framework that utilizes approximations to carefully select representative features of the source of the bio-signals for characterization and/or manipulation of the underlying biological system.

For each module, robust AI models are created and trained on suitably formatted data aggregated as described herein. The AI models could incorporate genetic, environmental, lifestyle, and other relevant information for more accurate representations of the circumstances of the participants. Fig. 1 illustrates the design of the system.

The AI models are built using four different approaches as follows:

1. Direct Use of LLMs such as GPT-4 as inference engines using the data collected, formatted as multidimensional input vectors. This could involve fine-tuning of the LLM.
2. Application of Prompt Engineering to LLMs such as Bard and GPT-4 (and their improved future iterations) to generate a series of steps for creating the AI-based system. The steps suggested by the LLM are then implemented using the creator's extensive knowledge of and experience with AI, neural networks, and deep learning with the Python programming language, the TensorFlow platform, the Keras API as well as other machine learning (ML), and visualization tools such as Scikit-learn and Matplotlib.

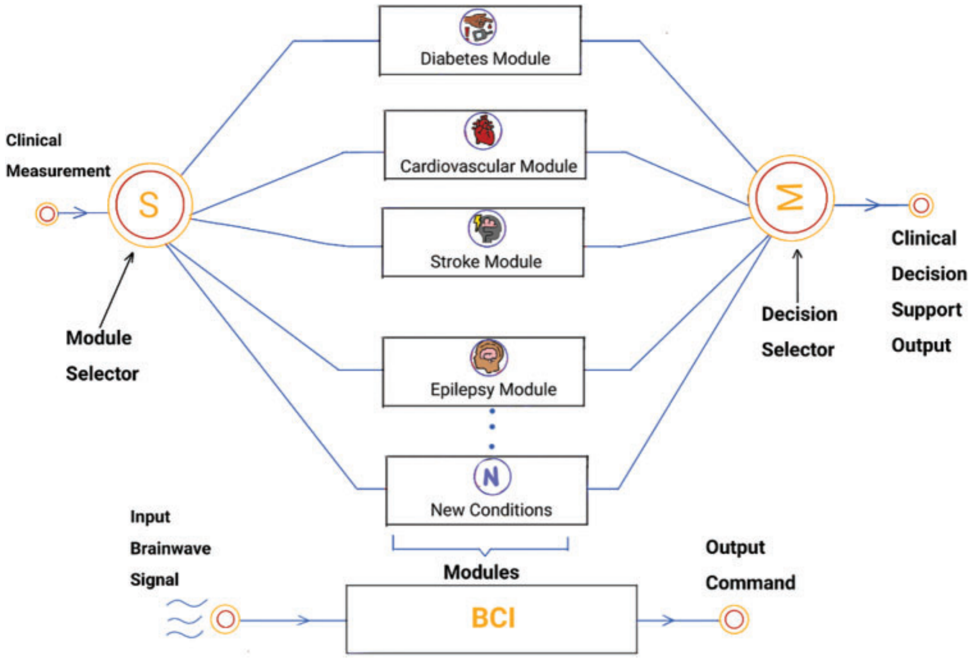

Fig. 1. System schematic design diagram for the comprehensive AI-Driven healthcare solution and brain computer interface system. The new conditions component represents additional health conditions that can be incorporated into the solution via new modules.

3. Generation of specific AI models utilizing the features of LLMs such as Bard and GPT-4 (and their improved future variants) via an automated model generation pipeline.
4. Direct synthesis of a suitable AI architecture based on the creator's extensive knowledge of and experience with AI, neural networks, and deep learning with the Python programming language, the TensorFlow platform, the Keras API as well as other ML and visualization tools such as Scikit-learn and Matplotlib.

All steps involved and tools used in the creation of the solution are rigorously documented to facilitate seamless transfer and reuse of the system.

The AI models generated are compared and contrasted in terms of their performance (using performance metrics such as specificity, sensitivity, and so on) and fit for the challenges encountered.

2.5. *Heart Disease Diagnosis Module*

This section highlights details of the implementation of a Heart Disease Diagnosis Module for the comprehensive AI-driven healthcare system.

Adopting the fourth approach outlined earlier, namely, direct creation of AI models based on a suitable AI architecture, the Heart Disease Diagnosis Module (as an illustrative example) comprises a 3-layer (1 Input Layer, 1 Hidden Layer, 1 Output Layer–dense layers with a sequential network topology) perceptron implemented by harnessing the TensorFlow platform and the Keras API in the Python programming language [47], [48]. The input layer contains 13 units or neurons representing 13 distinct clinical measurements for the participant including resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic (ECG) results, maximum heart rate, exercise-induced angina presence, ST depression induced by exercise relative to rest, the slope of peak exercise ST segment, number of major vessels (0–3) colored by fluoroscopy, heart performance, sex and age of the participant. The output layer contains 1 unit or neuron representing the diagnosis indicating the presence or absence of heart disease. With extensive experimentation, 128 units of neurons were utilized for the hidden layer. Apart from the output layer where sigmoid activation units were adopted, rectified linear units were harnessed throughout the neural network.

A generalized graphical representation of the core features of the artificial neural network is depicted in Fig. 2.

The Cleveland Heart Disease dataset publicly available from the University of California Irvine Machine Learning Repository was used for training, testing, and validation of the artificial neural network. Incomplete entries were removed from the dataset, leaving a total of 297 rows of data each containing 14 columns where the first 13 columns of each row represent clinical measurements

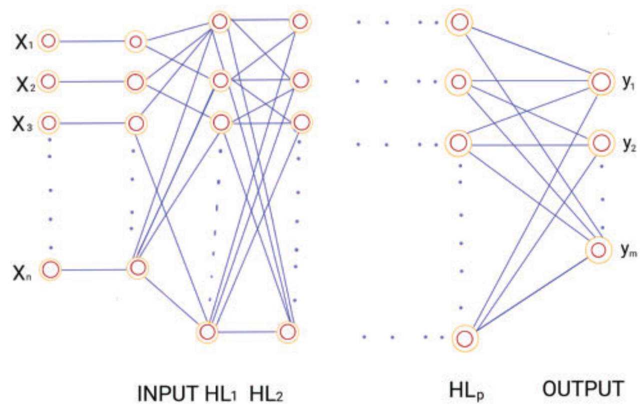

Fig. 2. Generalized graphical representation of artificial neural network (ANN) architecture. X1, X2, . . . , Xn depict inputs; HL1, HL2, HLp depict hidden layers while Y1, Y2, Ym depict outputs.

(for a distinct participant) such as resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic (ECG) results, and so on. The last or fourteenth column represents the diagnosis (for the distinct participant represented by the selected row of data) with a value of 0 indicating normal heart function while values 1, 2, 3, and 4 indicate the presence of heart disease. Posed as a binary classification problem (absence: 0 or presence:1 of heart disease), the target classification task requires the encoding of the last or fourteenth column as a binary number with 0 mapping to a value of 0 and 1, 2, 3, and 4 mapping to a value of 1.

2.6. *Data Availability*

The data utilized in this study are available from **GitHub** at https://github.com/frankekpar/cleveland_heart_disease_dataset/blob/main/dataset.zip and derived from the Cleveland Heart Disease dataset publicly available from the University of California Irvine Machine Learning Repository at https://archive.ics.uci.edu/.

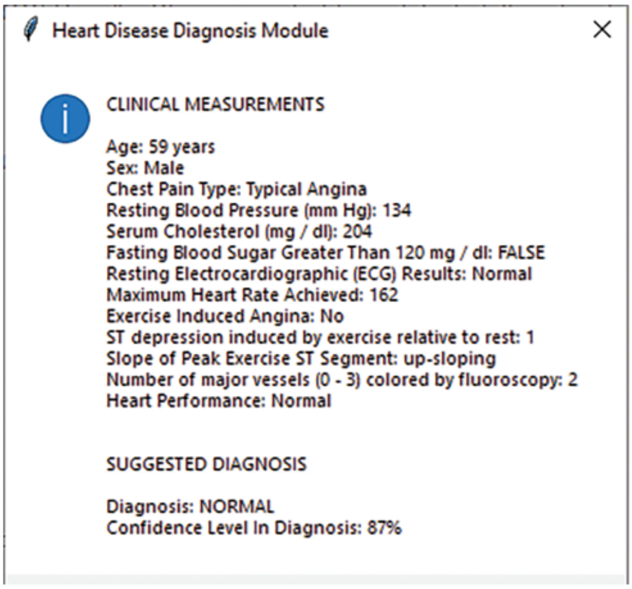

Fig. 3. Heart disease diagnosis module of scholar medic showing clinical measurements and corresponding suggested diagnosis.

3. Results

In the current instance, seventy per cent (70%) of the Cleveland Heart Disease dataset was set aside for model training while 30% of the dataset was reserved for model testing and validation. The neural network was optimized via the Adam optimizer [49], [50] and trained on the training dataset for 500 epochs relying on the binary cross-entropy loss function. The learning rate employed was 0.001 while the batch size was 32.

The performance of the model on the validation dataset was characterized by a precision of 87%, a sensitivity or recall of 75%, and a specificity of 90%.

The trained model could be adopted in the Heart Disease Diagnosis Module and incorporated into Scholar Medic, the comprehensive AI-driven healthcare system resulting from the work reported here.

Fig. 3 is a screenshot from the Heart Disease Diagnosis Module in the Scholar Medic with a listing of the clinical measurements obtained from a selected participant and the suggested diagnosis.

Precision, sensitivity or recall, and specificity performance metrics are defined as indicated in the following equations.

$$Precision = \frac{TP}{TP + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

In the foregoing equations, TN refers to true positives, FP refers to false positives, FN refers to false negatives, and TN refers to true negatives. Negative here indicates normal heart functioning or the absence of heart disease while positive indicates the presence of heart disease.

The adoption of the comprehensive AI system described here will lead to the availability of actionable insights for clinical decision support will save lives, and improve living conditions by reducing the economic, social, psychological, and physical burden of the conditions so predicted and possibly prevented, detected early, diagnosed, treated and managed more efficiently.

Electronic Health Records (EHR) comprising clinical diagnostic measurements and EEG data could be generated by the participating medical doctors and affiliated colleagues. Electroencephalography (EEG) data could also be generated in the context of experiments involving BCIs. These data are collected in accordance with the ethical clearance obtained and anonymized before publication in publicly accessible repositories alongside scholarly research articles.

4. Discussion

Predictions could be used to inform recommendations for lifestyle changes that could lead to the prevention of diseases and vastly improved health outcomes.

The system's modular design allows for the potential diagnosis and prediction of additional conditions in the future and efficient updates to specific modules using fresh data.

Environmental and genetic data could also be incorporated into the AI models to more accurately represent the living conditions of the participants and to render the medical practitioner's prescriptions more efficacious.

A wide range of approaches including the use of large language models and smaller scale AI models could be adopted, compared, and contrasted with the best approach in light of resource availability and expediency ultimately implemented under any given circumstances.

Further enhancement of the technologies presented here through extended research and development activities (including manufacturing the novel three-dimensional multilayer EEG system [45], [46] introduced by Ekpar potentially permitting orders of magnitude higher electrode densities and better performance than conventional

EEG systems) will expand the capabilities of society, lead to rehabilitation of those suffering from neurological conditions and generally improve the standard of living.

5. Conclusion

This paper presented a comprehensive AI-driven healthcare system that could save lives and improve living conditions by assisting medical practitioners via clinical decision support in the prediction and diagnosis of a wide variety of conditions. Augmentation with lifestyle, genetic and environmental information providing more accurate representations of the participant's environment could lead to improved health outcomes while local data drives facilitate the reduction of bias and enhancement of the global relevance of the system's outputs. Featuring a modular design, the system is amenable to the incorporation of modules for the prediction and diagnosis of additional conditions in the future as well as the implementation of efficient improvements to existing modules.

Conflict of Interest

Author declares no conflict of interest.

References

[1] World Health Organization (WHO). Diabetes statistics. Available from: https://www.who.int/news-room/fact-sheets/detail/diabetes. 2023.

[2] World Health Organization (WHO). Epilepsy statistics. Available from: https://www.who.int/news-room/fact-sheets/detail/epilepsy. 2024.

[3] World Health Organization (WHO). Cardiovascular diseases statistics. Available from: https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1. Accessed: 2023.

[4] World Health Organization (WHO). Stroke, cerebrovascular, accident statistics. Available from: https://www.emro.who.int/health-topics/stroke-cerebrovascular-accident/index.html. Accessed: 2023.

[5] Nomura A, Noguchi M, Kometani M, Furukawa K, Yoneda T. Artificial intelligence in current diabetes management and prediction. *Curr Diab Rep*. 2021;21(12):61.

[6] Kumar Y, Koul A, Singla R, Ijaz MF. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. *J Ambient Intell Humaniz Comput*. 2023;14:8459–86.

[7] Ansari S, Shafi I, Ansari A, Ahmad J, Shah SI. Diagnosis of liver disease induced by hepatitis virus using artificial neural network. *IEEE Int Multitopic*. 2011:8–12. doi: 10.1109/INMIC.2011.6151515.

[8] Battineni G, Sagaro GG, Chinatalapudi N, Amenta F. Applications of machine learning predictive models in the chronic disease diagnosis. *J Personal Med*. 2020;10(2):21. doi: 10.3390/jpm10020021.

[9] Abdar M, Yen N, Hung J. Improving the diagnosis of liver disease using multilayer perceptron neural network and boosted decision tree. *J Med Biol Eng*. 2018;38:953–65.

[10] Chaikijurajai T, Laffin L, Tang W. Artificial intelligence and hypertension: recent advances and future outlook. *Am J Hypertens*. 2020;33:967–74.

[11] Fujita S, Hagiwara A, Otsuka Y, Hori M, Takei N, Hwang KP, *et al.* Deep learning approach for generating MRA images from 3D quantitative synthetic MRI without additional scans. *Invest Radiol*. 2020;55:249–56.

[12] Juarez-Chambi RM, Kut C, Rico-Jimenez JJ, Chaichana LK, Xi J, Campos-Delgado DU, *et al.* AI-assisted *in situ* detection of human glioma infiltration using a novel computational method for optical coherence tomography. *Clin Cancer Res*. 2019;25(21):6329–38.

[13] Nashif S, Raihan R, Islam R, Imam MH. Heart disease detection by using machine learning algorithms and a real-time cardiovascular health monitoring system. *World J Eng Technol*. 2018;6(4):854–73.

[14] Chen PHC, Gadepalli K, MacDonald R, Liu, Kadowaki S, Nagpal K, Kohlberger T, *et al.* An augmented reality microscope with real time artificial intelligence integration for cancer diagnosis. *Nat Med*. 2019;25:1453–7.

[15] Gouda W, Yasin R. COVID-19 disease: CT Pneumonia Analysis prototype by using artificial intelligence, predicting the disease severity. *Egypt J Radiol Nucl Med*. 2020;51(1):196.

[16] Han Y, Han Z, Wu J, Yu Y, Gao S, Hua D, *et al.* Artificial intelligence recommendation system of cancer rehabilitation scheme based on IoT technology. *IEEE Access*. 2020;8:44924–35.

[17] Chui CS, Lee NP, Adeoye J, Thomson P, Choi SW. Machine learning and treatment outcome prediction for oral cancer. *J Oral Pathol Med*. 2020;49(10):977–85.

[18] Koshimizu H, Kojima R, Okuno Y. Future possibilities for artificial intelligence in the practical management of hypertension. *Hypertens Res*. 2020;43:1327–37.

[19] Kather JN, Pearson AT, Halama N, Jäger D, Krause J, Loosen SH, *et al.* Deep learning microsatellite instability directly from histology in gastrointestinal cancer. *Nat Med*. 2019;25:1054–6.

[20] Kwon JM, Jeon KH, Kim HM, Kim MJ, Lim SM, Kim KH, *et al.* Comparing the performance of artificial intelligence and conventional diagnosis criteria for detecting left ventricular hypertrophy using electrocardiography. *EP Eur*. 2020;22(3):412–9.

[21] Khan MA. An IoT framework for heart disease prediction based on MDCNN classifier. *IEEE Access*. 2020;8:34717–27.

[22] Oikonomou EK, Williams MC, Kotanidis CP, Desai MY, Marwan M, Antonopoulos AS, *et al.* A novel machine learning-derived radiotranscriptomic signature of perivascular fat improves cardiac risk prediction using coronary CT angiography. *Eur Heart J*. 2019;40(43):3529–43.

[23] Sabottke CF, Spieler BM. The effect of image resolution on deep learning in radiography. *Radiol: Artif Intell*. 2020;2(1, 2):e190015.

[24] Brown T, Mann B, Ryder N, Subbiah M, Kaplan JD, Dhariwal P, *et al.* Language models are few-shot learners. *Adv Neur Inf Process Syst*. 2020;33:1877–901.

[25] Gurnee W, Tegmark M. Language models represent space and time. [Digital Preprint] *arXiv:2310.02207*. 2023. doi: 10.48550/arXiv.2310.02207.

[26] Padfield N, Zabalza J, Zhao H, Masero V, Ren J. EEG-based brain-computer interfaces using motor-imagery: techniques and challenges. *Sensors*. 2019;19:1423.

[27] Kevric J, Subasi A. Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system. *Biomed Signal Process Control*. 2017;31:398–406.

[28] Cho H, Ahn M, Ahn S, Kwon M, Jun SC. EEG datasets for motor imagery brain-computer interface. *GigaScience*. 2017;6(7):1–8.

[29] Arpaia P, Esposito A, Natalizio A, Parvis M. How to successfully classify EEG in motor imagery BCI: a metrological analysis of the state of the art. *J Neur Eng*. 2022;19:031002.

[30] Kaya M, Binli MK, Ozbay E, Yanar H, Mishchenko Y. A large electroencephalographic motor imagery dataset for electroencephalographic brain computer interfaces. *Sci Data*. 2018;5:180211.

[31] Tibrewal N, Leeuwis N, Alimardani M. Classification of motor imagery EEG using deep learning increases performance in inefficient BCI users. *PLoS One*. 2022;17(7):e0268880.

[32] Sreeja SR, Rabha J, Nagarjuna KY, Samanta D, Mitra P, Sarma M. Motor imagery EEG signal processing and classification using machine learning approach. *IEEE International Conference on New Trends in Computing Sciences (ICTCS)*, 2017.

[33] Das K, Pachori RB. Electroencephalogram-based motor imagery brain-computer interface using multivariate iterative filtering and spatial filtering. *IEEE Trans Cogn Dev Syst*. 2022;15(3):1408–18.

[34] Velasco I, Sipols A, Simon De Blas C, Pastor L, Bayona S. Motor imagery EEG signal classification with a multivariate time series approach. *Biomed Eng Online*. 2023;22:29.

[35] Yang A, Lam HK, Ling SH. Multi-classification for EEG motor imagery signals using data evaluation-based auto-selected regularized FBCSP and convolutional neural network. *Neur Comput Appl*. 2023;35:12001–27.

[36] Venkatachalam K, Devipriya A, Maniraj J, Sivaram M, Ambikapathy A, Amiri IS. A novel method of motor imagery classification using EEG signal. *Artif Intell Med*. 2020;103:101787.

[37] Subasi A, Gursov MI. EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Syst Appl*. 2010;37(12):8659–66.

[38] Razzak I, Hameed IA, Xu G. Robust sparse representation and multiclass support matrix machines for the classification of motor imagery EEG signals. *IEEE J Trans Eng Health Med*. 2019;7:2000508.

[39] Pahuja SK, Veer K. Recent approaches on classification and feature extraction of EEG Signal: A review. *Robotica*. 2022;40(1):77–101.
[40] Lekshmi SS, Selvam V, Rajasekaran MP. EEG signal classification using principal component analysis and wavelet transform with neural network. *IEEE International Conference on Communication and Signal Processing*, 2014.
[41] Lugger K, Flotzinger D, Schlögl A, Pregenzer M, Pfurtscheller G. Feature extraction for on-line EEG classification using principal components and linear discriminants. *Med Biol Eng Comp*. 1998;36(3):309–14.
[42] Lawhern VJ, Solon AJ, Waytowich NR, Gordon SM, Hung CP, Lance BJ. EEGNet: a compact convolutional neural network for EEG-based brain-computer interfaces. *J Neur Eng*. 2018;15:056013.
[43] Al-Saegh A, Dawwd SA, Abdul-Jabbar JM. Deep learning for motor imagery EEG-based classification: a review. *Biomed Signal Process Control*. 2021;63:102172.
[44] Tabar YR, Halici U. A novel deep learning approach for classification of EEG motor imagery signals. *J Neur Eng*. 2016;14:016003.
[45] Ekpar FE. System for nature-inspired signal processing: principles and practice. *Eur J Electr Eng Comput Sci*. 2019;3(6):1–10.
[46] Ekpar FE. A novel three-dimensional multilayer electroencephalography paradigm. *Research Square*. 2023. doi: 10.21203/rs.3.rs-3003621/v1.
[47] Abadi M, Barham P, Chen J, Chen Z, Davis A, Dean J, *et al.* TensorFlow: A system for large scale machine learning. *Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI '16)*, 2016.
[48] Pang B, Nijkamp E, Wu YN. Deep learning with TensorFlow: A review. *J Educ Behav Stat*. 2019;45(2):227–48.
[49] Kingma DP, Ba JL. Adam: A method for stochastic optimization. *International Conference on Learning Representations (ICLR)*, 2015.
[50] Zhang Z. Improved adam optimizer for deep neural networks. *IEEE/ACM 26th International Symposium on Quality of Service (IWQoS)*, 2018.